

# On-Chart Success Dynamics of Popular Songs

Seungkyu Shin and Juyong Park

*Graduate School of Culture Technology and BK21 Plus Postgraduate Programme for Content Science,  
Korea Advanced Institute of Science & Technology, Daejeon, Republic of Korea 34141*

In the modern era where highly-commodified cultural products compete heavily for mass consumption, finding the principles behind the complex process of how successful, “hit” products emerge remains a vital scientific goal that requires an interdisciplinary approach. Here we present a framework for tracing the cycle of prosperity-and-decline of a product to find insights into influential and potent factors that determine its success. As a rapid, high-throughput indicator of the preference of the public, popularity charts have emerged as a useful information source for finding the market performance patterns of products over time, which we call the on-chart life trajectories that show how the products enter the chart, fare inside it, and eventually exit from it. We propose quantitative parameters to characterise a life trajectory, and analyse a large-scale data set of nearly 7000 songs from Gaon Chart, a major weekly Korean Pop (K-Pop) chart that cover a span of six years. We find that a significant role is played by non-musical extrinsic factors such as the might of production companies and possibly established fan base in the on-chart success of songs, strongly indicative of the commodified nature of modern cultural products. We also discuss several nontrivial yet intriguing trajectories that we call the “Late Bloomers” and the “Re-entrants” that appears to be strongly driven by serendipitous exposure on mass media and the changes of seasons.

## I. INTRODUCTION

Competition for survival and success is a crucial mechanism underlying the evolution of species or actors in a complex system, be it biological, social, or technological [1–3]. The increasing availability of large-scale data along with a remarkable progress in the theory and modeling of complex systems has led to the emergence of the “science of success” that aims to reveal common patterns in the success of people or products in such diverse subjects as viral spreading of content, performance of athletes in sports, popularity of emergent technologies, and impact of scientific works [4–7].

The scientific study of success is also deeply related to the tradition of developing robust and effective ranking methods for identifying the most successful and superior actors in a competition system [8–12]. Rankings of products and commodities serve a useful purpose for customers looking to purchase, or firms planning to advertise and market products. Cultural products such as popular songs are no exception, especially in this day and age where digital communication technology has enabled massive and efficient dissemination and consumption. Popularity charts have accordingly become more instantaneously updated, emerging as an essential reference for customers trying to make decisions in the face of a flood of new content and information, therefore becoming a coveted platform that affords products more exposure and prolonged success [13–16]. This brings up the hope that we may now be able to search for answers to many interesting questions into the underlying mechanisms of successful products, including “What are the features of ‘hit’ products that can be learnt from their chart dynamics?”, “What are the factors—intrinsic or extrinsic—behind the success of products?”, and so forth.

In this paper, as an attempt to answer these questions using high-quality contemporary data and scientific

methodology, we study the chart dynamics of K-Pop (Korean pop) songs, i.e. how the songs fare on popularity charts and what factors are behind it. K-Pop, a relatively recent international cultural sensation from South Korea, is characterised by catchy tunes and a heavy use of audiovisual elements. One of the early pinnacles of its global success happened in July of 2012 with PSY’s *Gangnam Style* that reached number two on the U.S. Billboard Hot 100. Its online success can be said to be even more phenomenal, scoring nearly three billion views on YouTube as of this writing (April 2017) to become the most-watched online video. Another prominent characteristic of K-Pop is the prominence of “idols”, young, highly-trained dancer-singers who are designed to be the hub around which an entire industry of production and merchandise/service providers are organised [17]. This type of intensive commercialisation places K-Pop at the forefront of the contemporary music industry where the intrinsic, musical properties of a song such as its melody or lyrics are relegated to being merely one factor that affects its success [18–21]. Prompted by this sweeping trend, in this paper we study a prominent K-Pop chart data to characterise the chart dynamics of successful songs, and then determine the extent to which such extrinsic factors correlated with their successes.

## II. POPULARITY CHARTS AND THE LIFE TRAJECTORY OF A PRODUCT

### A. Data, basic methodology, and life trajectory patterns

We analyze the data from Gaon Music Charts ([www.gaonchart.co.kr](http://www.gaonchart.co.kr)), a collection of weekly music charts serviced by the association of Korea’s music industry. We focus on the Gaon Digital Chart,

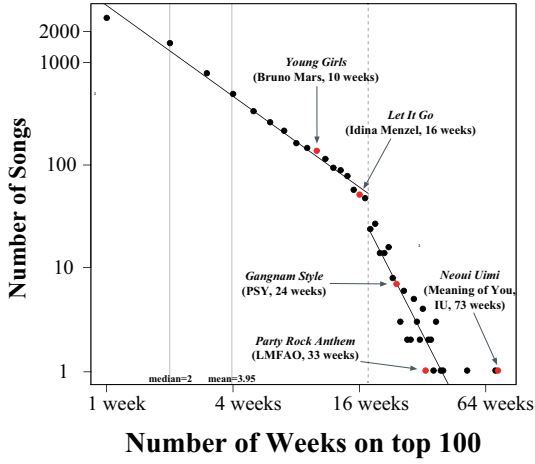


FIG. 1. Histogram of the number of weeks spent by the songs on the Gaon Digital Chart that exhibits a highly skewed behavior. The mean is 3.95 and the median is 2 for the songs that spend at least one week on the chart. The longest is for IU's *Neoui Uimi* (The Meaning of You) at 73 weeks.

the signature one similar in spirit to the U.S. Billboard Hot 100. It ranks the top-100 songs (both domestic K-Pop and foreign songs in a single chart) according to their digital sales figures including downloads, online streaming counts, *etc.* Our data covers all weeks between the second week of 2010 (the actual beginning of Gaon) and the 53rd week of 2015, for a total of 313 weeks. During this period there have been in total 7560 songs that appeared at least once on the chart. The actual numbers of weeks spent on the chart, however, vary widely as shown in Fig. 1: 36.4% of the songs (2750) appeared for one week only, whereas 9.1% of the songs (689) stayed on the chart more than ten weeks. The longest life on the chart was enjoyed by IU's *Neoui Uimi* (The Meaning of You) for a record of the 73 weeks. The same artist's *Joeun Nal* (Good Day) and PSY's *Gangnam Style* topped the chart at number one for the most weeks (5).

For most songs that do appear in the chart, the weekly rankings follow roughly a similar pattern (notable exceptions are discussed later): It appears in the chart, reaches its peak rank at some point, declines, and eventually leaves the chart. Upon inspection of numerous curves made by the songs' rankings, we find it useful to characterise such **life trajectory** of a song via the following parameters:

$r_{\text{init}}$	Song's inaugural rank on the chart [22]
$r_{\text{max}}$	Peak rank
$t_{\text{pre}}$	Time taken to reach the peak since inaugural appearance on chart
$t_{\text{post}}$	Time taken to exit from chart since peak rank

(a) Four parameters of a song's life trajectory

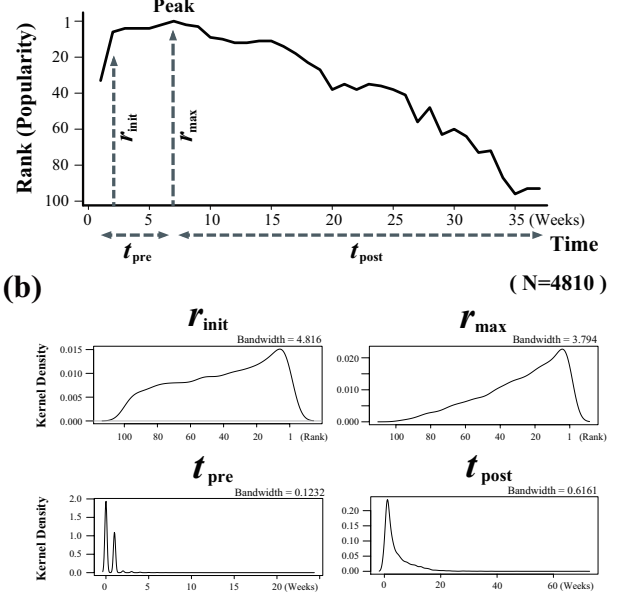


FIG. 2. (a) Four parameters that describe a song's life trajectory on a chart: inaugural rank ( $r_{\text{init}}$ ), peak rank ( $r_{\text{max}}$ ), time spent on the chart before peak rank ( $t_{\text{pre}}$ ), and time spent on the chart after its peak ( $t_{\text{post}}$ ). (b) The distribution density of the four parameters estimated using Kernel Density Estimation (KDE) method. The  $r_{\text{init}}$  and  $r_{\text{max}}$  are weighted towards high values, whereas  $t_{\text{pre}}$  and  $t_{\text{post}}$  are weighted towards low values. Songs that appeared on the chart for two weeks or more (4810 songs in total, see definition of  $r_{\text{init}}$  in Table) were analyzed to generate these figures.

An example is shown in Fig. 2(a) for girlband EXID's *Wiarae* (Up and Down). It first entered the chart at  $r_{\text{init}} = 7$ , reaching its peak ( $r_{\text{max}} = 1$ )  $t_{\text{pre}} = 6$  weeks later, then fell gradually (save for some brief rallies) for  $t_{\text{post}} = 30$  weeks until it left the chart. In Fig. 2(b) we show the probability density function of the four parameters using kernel density estimation (KDE) method.  $r_{\text{init}}$  and  $r_{\text{max}}$  are slightly skewed towards high values whereas  $t_{\text{pre}}$  and  $t_{\text{post}}$  are more heavily skewed towards lower values, meaning that an overwhelming majority of songs enjoy only brief stints on the chart.

The relationships between the parameters reveal more interesting patterns about the trajectories of the songs, presented in Fig. 3 and 4. In Fig. 3(a), the inaugural ranks  $\{r_{\text{init}}\}$  are plotted along the  $x$ -axis, and the difference between the initial rank and maximum ranks  $\{r_{\text{init}} - r_{\text{max}}\}$  are plotted along the  $y$ -axis. The data points appear to be roughly evenly spread out here with the exception of a high density of points along the horizontal  $r_{\text{init}} = 0$ , meaning that for many songs the inaugural rank was indeed the peak. In Fig. 3(b), the time until the peak  $\{t_{\text{pre}}\}$  are plotted along the  $x$ -axis, and the time until exiting the chart since the peak  $\{t_{\text{post}}\}$  are plotted along the  $y$ -axis. Since most songs stay on the chart for only a short period of time as shown in Fig. 1,

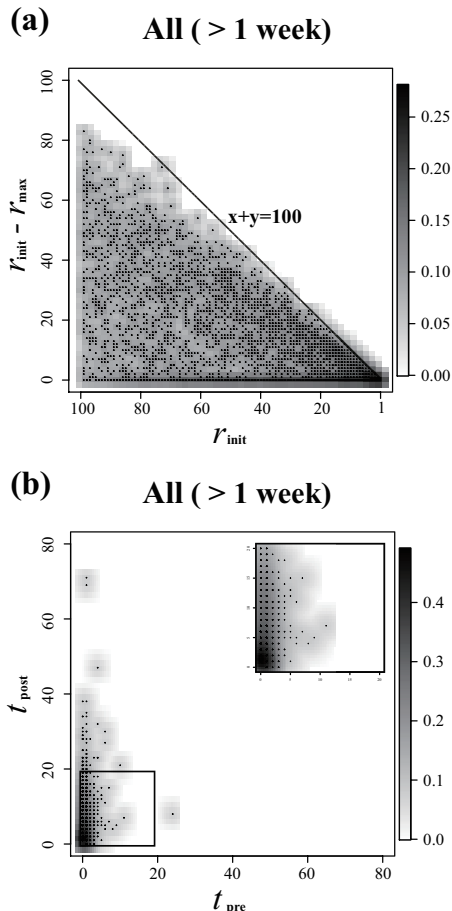


FIG. 3. The life trajectory parameters of the songs on the chart. (a) The inaugural rank is plotted along the  $x$ -axis, and the difference between the inaugural and peak ranks is plotted along the  $y$ -axis. (b) The amount of time taken to reach the peak is plotted along the  $x$ -axis, and the amount of time taken to first go off the chart after reaching the peak is plotted along the  $y$ -axis.

they are largely concentrated in the bottom left area. But overall  $t_{\text{post}} > t_{\text{pre}}$ , meaning that for most songs the decay is longer than ascension.

When we study the more successful, “hit” songs, distinct patterns emerge. In Fig. 4(a) and (b) we show analogous plots for the 689 songs that stayed on the chart for longer than ten weeks, accounting for 9.1% of the songs in the full data set. In Fig. 4(a) we see that now the songs occupy the bottom right side, meaning that successful songs are likely to be already ranked high in its early phase, implying that a song’s potential for on-chart success is realised at the very beginning, and appearing on the chart does not necessarily translate to opportunity for attaining a higher rank. The message is similar in Fig. 4(b) where  $t_{\text{pre}}$  ( $x$ -axis) ranges merely between one and ten weeks (with the exception of *Rock Party Anthem* by LMFAO which is not a K-Pop but a foreign song, which we will discuss later in more detail) while  $t_{\text{post}}$  on the  $y$ -axis assume much wider values with the

maximum of 71 weeks. Consider PSY’s *Gangnam Style* and IU’s *Neoui Uimi* in Fig. 4(g) A and B that do show typical behaviors of K-Pop: Both take no to a very short time on the chart to reach their peaks.

We also find that foreign songs tend to show a noticeably different general behavior from that of K-Pop. Take *New Thang* by Redfoo and *Party Rock Anthem* by LMFAO, for instance, that are the outliers in Fig. 4(a) and (b). *New Thang* entered the chart at  $r_{\text{init}} = 83$ , rising in the chart quite slowly (see Fig. 4(g) C), peaking at  $r_{\text{max}} = 65$  and staying on the chart for a total of 11 weeks. *Party Rock Anthem*, on the other hand, took  $t_{\text{pre}} = 24$  weeks to peak, but exited the chart in  $t_{\text{post}} = 8$  weeks. In fact, the other outliers in the plots of Fig. 4(a) and (b) tend to be foreign songs as well, taking a longer time to reach their peaks than K-Pop songs: Two out of five songs above  $y = x$  in Fig. 4(a) are foreign songs, and below  $y = x$  in Fig. 4(b) (meaning  $t_{\text{pre}} > t_{\text{post}}$ ), four out of the seven songs were foreign although only 5.41% (260) of the songs analyzed (4810) are foreign.

## B. Chart dynamics of K-Pop vs foreign songs

We now take a deeper look at the differences between K-Pop and foreign songs. To do so we analyze two separate subcharts of Gaon, primarily due to the small sample size of foreign songs in the original data: Of the  $N = 7560$  songs that ever appeared in the main Gaon digital chart, only three percent (260) are foreign. The subcharts we use here are the digital top-100 charts exclusively for K-Pop and foreign songs. This yields a much larger set of foreign songs for us to analyze: 7602 for K-Pop (there is not much difference, since the main chart was dominated by domestic songs to begin with), and 3855 for foreign songs. Again focusing on those that survived for more than ten weeks on each chart (702 K-Pop and 327 foreign songs), we find that the total life on the chart already show significant differences: K-Pop songs survive on average  $15.7 \pm 0.4$  weeks with maximum 73 weeks by IU’s *Neoui Uimi*, while foreign songs survive  $37.3 \pm 1.0$  with a maximum of 235 weeks by Maroon 5’s *Moves Like Jagger* (Fig. 4(g) E).

Their life trajectories are plotted separately in Figs. 4(c) to (f). They again confirm that K-Pop songs reach their peaks early, with only 2.14% entering the chart under the 40th place, and the longest  $t_{\text{pre}}$  is equal to ten, for *Geu namjan marya* (Because of You) by M.C the Max. Foreign songs on the other hand, while fewer than half the number of K-Pop in total, show a wider distribution of the parameters in Fig. 4(e) and (f): 18.7% entered the chart ranked 40th or lower, and 46 songs took more than ten weeks to reach their peaks, with maximum  $t_{\text{pre}} = 220$  by Adele’s *Someone Like You* that entered the chart at  $r_{\text{init}} = 98$ .

The question is, then, which factors are behind such visible differences between K-Pop and foreign songs. One

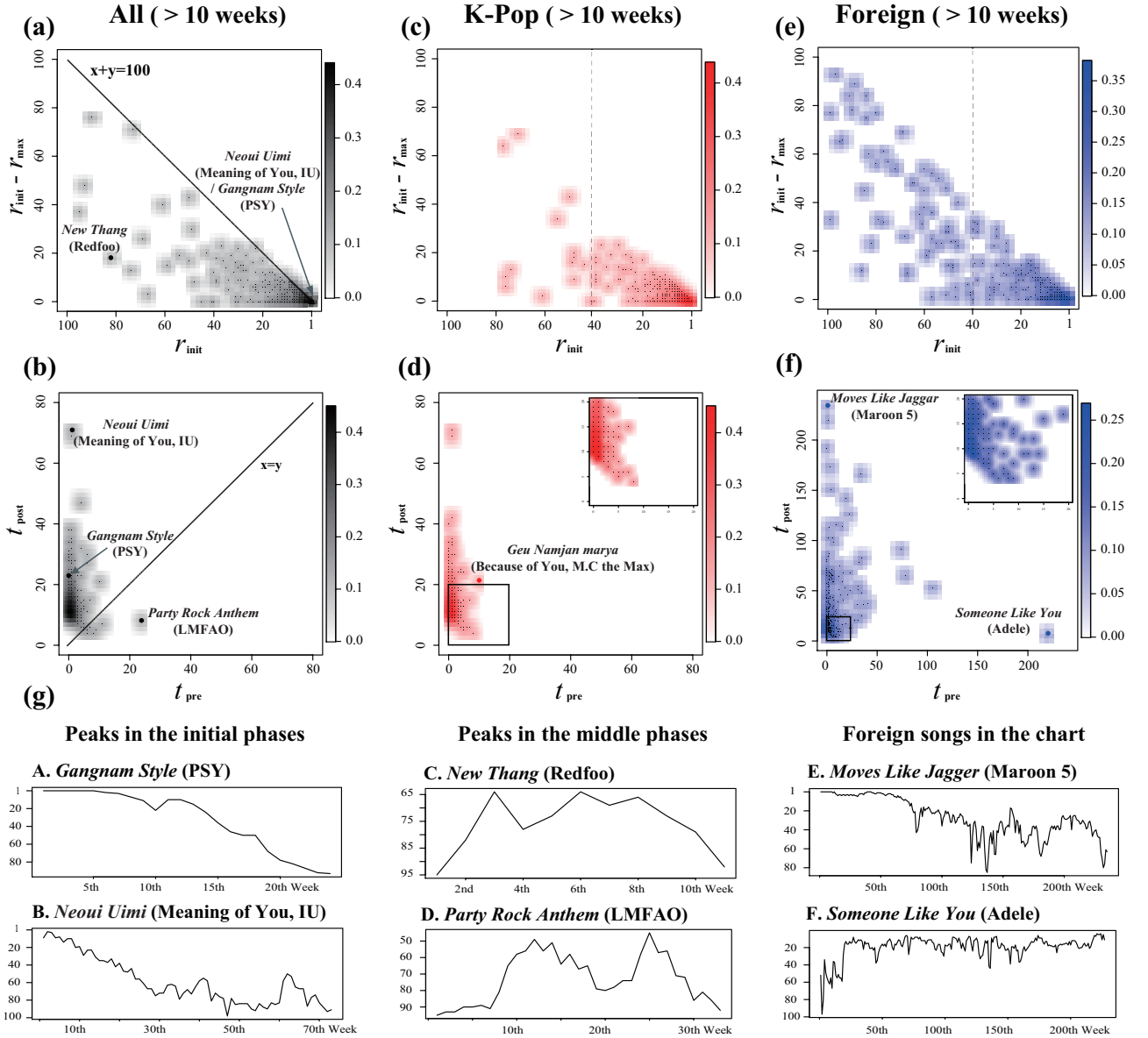


FIG. 4. The life trajectory parameters of 689 successful songs (defined as longer than ten weeks on the chart). (a) The bulk of the songs are located on the bottom right, meaning that a majority of songs that appear on the chart are ranked high in the early phases. (b) For most songs  $t_{\text{pre}}$  ranges up to ten weeks while  $t_{\text{post}}$  is much more wide-ranging with a maximum of 71 weeks. (c)-(f) The same plots for K-Pop (domestic) songs (red) and foreign songs (blue). Foreign songs are comparatively more spread out, probably due to less influence of extrinsic factors.

could argue that it could be the music itself, if there really are intrinsic differences between K-Pop and foreign pop. Even if such differences from a musical standpoint did exist at all, however, they would be quite subtle, given that nearly all modern popular genres—rock and roll, ballads, synth pop, electronica, *etc.*—in foreign pop are also well represented in K-Pop. We therefore find it unconvincing that the musical differences would be the sole determinant of the differences in the chart dynamics of songs. If not the intrinsic properties, then some external factors may be in play here. While there could be many, here we study one that is widely believed to be a defining

characteristic of contemporary K-Pop, the machinery of production companies.

### III. PRODUCTION COMPANIES AND K-POP

The observed fact that most songs reach their peaks in the very early phases of their lives does seem unnatural and counterintuitive—this means that the songs have already realised potential for success during the one short week before entering the chart or, even more bizarre, before its release. We believe that the clues to the origin

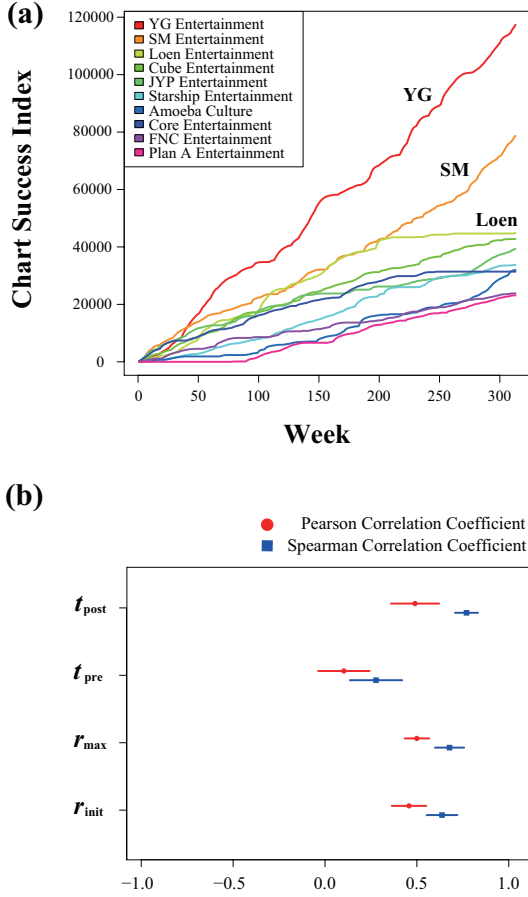


FIG. 5. (a) The growth of chart success index  $S$  of top 10 production companies. (b) Correlation between the chart success index and average life trajectory parameters of song released by the companies. The errors are estimated using the jack-knife method. All parameters except  $t_{\text{pre}}$  are positively correlated.

of such behavior comes from a dominant recent trend in how new K-Pop songs are produced and marketed: Production companies are increasingly focusing on pre-release marketing to rally the fandom that prop up on-line streaming counts and downloads in the very early stages of the song’s release [17]. This means that production companies in K-Pop—influential entities that recruit, train, finance, manage, and market artist and their public activities—may hold significant sway over the chart success of new songs [23, 24], possibly even more than their qualities may. Producers of foreign pop songs, on the other hand, generally do not maintain such a strong presence in Korea which explains their more natural dynamics on the charts (Fig. 4(e) and (f)).

We now investigate the influence of production companies on a song’s chart dynamics. We start by defining a quantity that represents the influence of a production company. Possible candidates could include the company’s sales volume, stock price, number of affiliated artists, etc. But here we focus on chart performance as

the measure of a company’s influence. In other words, we posit that a history of chart success is an indicator of the company’s influence and future success. This is inspired by the so-called “Matthew effect”, the rich-get-richer phenomena often observed in social systems [25]. We define the **Chart Success Index**  $S_i$  of a company  $i$  as the sum total of the weekly ranks of all songs produced by the company in the history of Gaon Digital Chart, i.e.

$$S_i \equiv \sum_{\substack{w \in \text{All Weeks} \\ s \in \Omega_i^w}} (101 - r_s^w), \quad (1)$$

where  $\Omega_i^w = \{s\}$  refers to all songs from company  $i$  ranked on the chart on week  $w$ , and  $r_s^w$  refers to the weekly rank of the song. Fig. 5(a) shows  $\{S\}$  of the ten most influential production companies during by the last week in our data set. Most companies display linear growth patterns, with YG Entertainment, SM Entertainment, and Loen Entertainment being the major three as of the last week in our data. To view the relationship between a company’s influence and the life trajectory of the songs they release, we compute the correlation coefficients between  $S$  and the four curve parameters. We note that here we consider the life trajectories of songs from *debuting* artists, because as unknowns we believe that their production companies’ abilities and clout would be the only major external, non-musical factor behind their chart performance. Of the 934 production companies that produced at least one new artist on the chart, 514 produced only one. To eliminate errors originating from such small samples, we consider the 55 companies that put nine or more debuting artists on the chart. The results are shown in Fig. 5(b). All parameters but the pre-peak time ( $t_{\text{pre}}$ ) show strong positive correlations with  $S$ . This means that having a powerful production company behind one’s back is highly correlated with general chart success at debut (i.e. long duration on chart and high peak rank), but regardless of the company’s influence the debuting artist hits their peak early. To a skeptical eye, this phenomenon may be a reason for doubting the role of the “quality” of a K-Pop song in its chart performance; since early peaking (short  $t_{\text{pre}}$ ) is universal while  $r_{\text{max}}$  is positively correlated with  $S$ ,  $r_{\text{max}}$  could be due simply to the marketing and the established fan base of a company—because it suggests that a K-Pop song’s success was somewhat determined even before its release, before it had a chance to be introduced to the larger consumer base—and  $t_{\text{post}}$  would also be a straightforward consequence of that (the higher the rank, the more time it takes to leave the chart). It should be noted, however, that this is not a complete picture, and there is still evidence that quality and musical properties do matter in a song’s chart success. Ironically, one could make the point from the dynamics of foreign songs in the Korean market that lack such a level of support and marketing from production companies: Foreign songs are slow to gain popularity, but they tend to have more staying power. It



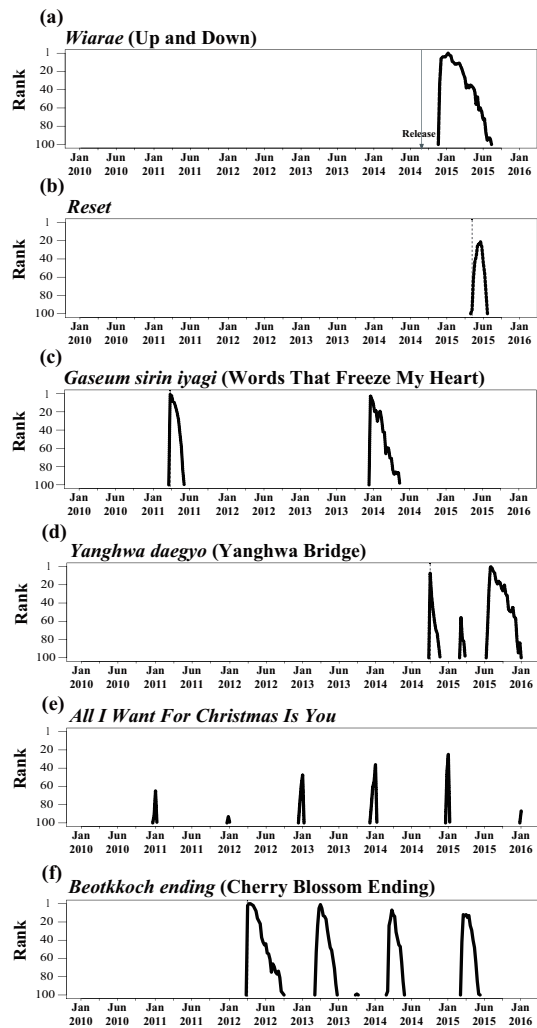


FIG. 6. (a) Two types of notable outlier types observed in chart dynamics. (a)–(b) The first type are “Late Bloomers,” referring to songs that climb up the chart or peak noticeably later than their market releases, often due to belated media exposure. (c)–(f) The second type are “Re-entrants,” referring to songs that re-enter a chart after leaving it. Media exposure and seasonal changes are the main factors.

may be an unsatisfactory state of affairs for the business that the effect of marketing may eclipse the importance of musical quality for K-Pop, and it remains to be seen how much role quality plays in the long run [26–28].

#### A. Other interesting patterns: Late Bloomers and Re-entrants

Against the general trend shown in Fig. 4 we can find some interesting patterns that do not conform to it, two of which we discuss here. The first class is “Late Bloomers” that take an relatively long time since debut to climb up the chart. This would be a very rare feat indeed: Only 1.5% of the songs (112 in total) manage to

climb in rankings for three straight weeks. A good example is *Wi-arae* (Up and Down) by EXID: having failed to make it to Gaon upon release, it went viral on other social networking sites before taking the 1st place several weeks later, as shown in Fig. 6(a). Another example is *Reset* by Korean-American rapper Tiger JK. The song was intended as a soundtrack to a TV drama whose popularity pushed up the song on to the charts, and its peak in the middle of its trajectory matches with the ratings peak for the TV show, see Fig. 6(b). The second class of extraordinary patterns is “Re-entrants”, referring to the songs that return to the chart after falling from it the first time (we consider a song’s life trajectory on the chart has come to an end when it exits the chart and does not return within five weeks.). A very small percentage of the songs (1.5%, or 116 songs) are such cases, and an even smaller number (39) stay on the chart for longer than five weeks after re-entry. A detailed review of the forces behind such behavior tells us that there are broadly two kinds: The first is renewed media exposure and broadcasting. Particularly, getting featured on audition programs such as *K-Pop Star* (Korean version of American Idol) or game shows centred on songs is a common way by which an old song experiences a surge of interest. *Gaseum Sirin Iyagi* (Words That Freeze My Heart) by Wheesung (Fig. 6(c)) and *Yanghwa daegyo* (Yanghwa Bridge) by Zion.T in Fig. 6(d) are famous examples helped by the mass media, sometime gaining even more popularity after re-entry than upon its release. The second is seasonal effect, which is very straightforward: Christmas carols such as *All I Want For Christmas Is You* by Mariah Carey (Fig. 6(e)) is a good example. The K-Pop song *Beotkkoch Ending* (Cherry Blossoms Ending) by Busker Busker, popular upon its release, is an example that became a spring carol of sorts that re-enters the chart every spring in Korea, as seen in Fig. 6(f).

## IV. DISCUSSION

In this paper, we have studied the life trajectories of K-Pop and foreign songs on Korea’s Gaon Charts. Most life trajectories could be represented with four parameters of their peak rankings and duration on the charts. A majority of songs, especially K-Pop, were found to attain their peaks in the early phases, which indicated the influence of non-musical external factors such as the power of production companies. There were evidence that, absent powerful production companies, quality and other factors such as media exposure could lead to chart success resulting in extraordinary life trajectories such as the late bloomers and the re-entrants.

We have demonstrated the possibility of utilizing popularity data to describe how the state of an industry affects the success of products, and we believe that the application is not necessarily limited to popular songs. We have explored only a small range of possibilities, and we hope to see our methods applied to more systems in a wider

gamut of products and markets.

## ACKNOWLEDGMENTS

This work was supported by the BK21 Plus Post-graduate Organisation for Content Science, IITP grant

funded by the Korean government (MSIP-R0115-16-1006), and National Research Foundation of Korea (NRF-20100004910, NRF-2016S1A2A2911945, and NRF-2016S1A3A2925033).

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